NOMADIC PEOPLE OPTIMIZER (NPO) FOR LARGE-SCALE OPTIMIZATION PROBLEMS

SINAN QAHTAN MOHAMD SALIH

DOCTOR OF PHILOSOPHY

UNIVERSITI MALAYSIA PAHANG

SUPERVISOR'S DECLARATION

We hereby declare that we have checked this thesis and in our opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Doctor of Philosophy.

____

(Supervisor's Signature)

Full Name : DR. ABDULRAHMAN A. ALSEWARI

Position : SENIOR LECTURER

Date : 18 FEB 2018

____

(Co-supervisor's Signature)

Full Name : DR. MOHAMAD FADLI ZOLKIPLI

Position : SENIOR LECTURER

Date : 18 FEB 2018

STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

____

(Student's Signature)

Full Name : SINAN QAHTAN MOHAMD SALIH

ID Number : PCC15005

Date : 18 FEB 2018

NOMADIC PEOPLE OPTIMIZER (NPO) FOR LARGE-SCALE OPTIMIZATION PROBLEMS

SINAN QAHTAN MOHAMD SALIH

Thesis submitted in fulfillment of the requirements
for the award of the Doctor of Philosophy
Degree in Computer Science

Faculty of Computer Systems & Software Engineering (FSKKP)

UNIVERSITI MALAYSIA PAHANG

FEBRUARY 2019

ACKNOWLEDGEMENTS

My sincere gratefulness and love to my housewife (Saba), my lovely son (Taym), and my daughter (Tara). For their endless love, prayers, sacrifice and support to pursue and successfully complete my studies.

To my family, thank you for encouraging me in all of my pursuits and inspiring me to follow my dreams. I am especially grateful to my parents, who supported me emotionally. I always knew that you believed in me and wanted the best for me. Thank you for teaching me that my job in life was to learn, to be happy, and to know and understand myself; only then could I know and understand others.

Foremost, I would like to express my sincere gratitude to my supervisor Dr. AbdulRahman A. Alsewari, and my Co-supervisor Dr. Mohamad Fadli Zolkipli for taking out time to ensure qualitative supervision of this research. Thanks a lot for your support and frequent feedback.

ABSTRAK

Beberapa dekad kebelakangan ini penyelidik telah menggunakan beberapa metodologi yang diilhamkan daripada masalah pengoptimuman yang kompleks. Kaedah carian berketentuan klasik diketahui sering terperangkap dalam minimum tempatan dan berprestasi kurang baik bagi masalah dimensi yang tinggi. Masalah lengkap-NP dianggap sebagai masalah pengoptimuman global yang umum; oleh itu, terdapat keperluan sumber pengkomputeran yang terlalu tinggi untuk memastikan pengiraan jitu bagi minimum global. Metaheuristik ditakrifkan sebagai satu proses generasi lelaran yang memberi petunjuk kepada sesuatu heuristik bawahan melalui gabungan konsep pintar yang berbeza untuk meneroka dan mengeksploitasi ruang penyelesaian; mereka menggunakan strategi pembelajaran untuk menstrukturkan maklumat dalam usaha menubuhkan penyelesaian hampir-optimum yang efisien. Tiga masalah besar dihadapi ketika merancang metaheuristik; masalah pertama ialah mengimbangi penerokaan dengan keupayaan eksploitasi (yang membawa kepada penumpuan pramatang atau memerangkap di dalam minimum tempatan), manakala masalah kedua adalah pergantungan algoritma tersebut kepada parameter mengawal, yang merupakan parameter dengan nilai-nilai optimum yang tidak diketahui. Masalah terakhir adalah keupayaan algoritma itu untuk menyelesaikan masalah skala-besar, yang kebanyakannya terdiri dari masalah dunia sebenar. Dalam tesis ini, suatu metaheuristik baru yang diilhamkan oleh alam semula jadi yang dipanggil "Pengoptimum Orang Nomad (NPO)" telah direka. NPO diilhamkan oleh gaya hidup nomad. Algoritma yang dicadangkan mensimulasikan tingkah laku nomad apabila mereka mencari sumber kehidupan (air atau padang ragut). Komponen asas algoritma tersebut terdiri daripada beberapa puak dan setiap puak mencari tempat yang terbaik (atau penyelesaian yang terbaik) berdasarkan kedudukan pemimpin mereka. Interaksi antara puak ini diilhamkan oleh konsep kumpulan (-kumpulan) orang yang dikuasai oleh pemimpin (-pemimpin) mereka. Para pemimpin puak secara berkala bertemu di dalam bilik untuk memilih pemimpin terbaik keseluruhan yang mempunyai kawalan ke atas semua pemimpin yang lain. "Pendekatan Bilik Mesyuarat (MRA)" ini memastikan keseimbangan antara keupayaan penerokaan dan eksploitasi NPO yang dicadangkan. NPO tersebut telah diuji dan dinilai berdasarkan enam puluh fungsi ujian tidak dikekang penanda aras. Tambahan lagi, kebolehskalaan NPO itu dinilai secara menyelesaikan lapan belas masalah berskala-besar. Keputusan eksperimen mengesahkan bahawa NPO yang dicadangkan berprestasi lebih baik daripada beberapa metaheuristik baru-baru ini dari segi mencapai penyelesaian terbaik, kebolehskalaan, kerumitan masa, dan kadar penumpuan. NPO ini berjaya menyelesaikan 52 daripada 60 fungsi ujian bersaiz normal manakala 16 dari 18 masalah berskala-besar telah sama-sama diselesaikan. Prestasi yang baik juga dicapai dengan NPO berkenaan dari segi hingar dan masalah maklumat yang terhad. Suatu ujian Wilcoxon Signed-Rank dilakukan untuk mengukur prestasi statistik pasangan bagi algoritma berkenaan dan daripada keputusan, NPO merekodkan prestasi statistik yang lebih baik berbanding dengan algoritma penanda aras yang lain. Dengan tegas boleh dinyatakan bahawa, penilaian eksperimen dan statistik yang dilakukan dalam kajian ini telah membuktikan keupayaan NPO yang dibangunkan ini untuk menyelesaikan masalah pengoptimuman dunia-sebenar.

ABSTRACT

Researchers have in the past few decades resorted to several methods that are inspired from complex optimization problems. The classical deterministic search methods are known to often get trapped in local minimum and do perform poorly on high dimensional problems. A metaheuristic is defined as an iterative generation process which guides a subordinate heuristic through a combination of different intelligent concepts for exploring and exploiting the solution space; they employ learning strategies to structure information in order to establish efficient near-optimal solutions. Three major problems are encountered when designing metaheuristics; the first problem is balancing exploration with exploitation capabilities (which leads to premature convergence or trapping in the local minima), while the second problem is the dependency of the algorithm on the controlling parameters, which are parameters with unknown optimal values. The final problem is the ability of the algorithm to solve large-scale problems, which mostly are the real world problems. In this thesis, a novel nature-inspired metaheuristic called "Nomadic People Optimizer (NPO)" was designed. The NPO is inspired by the lifestyle of the nomads. The proposed algorithm simulates the behavior of the nomads when they are searching for life sources (water or grazing fields). The basic component of the algorithm consists of several clans and each clan searches for the best place (or best solution) based on the position of their leader. The interaction between these clans is inspired by the concept of a group(s) of people controlled by their leader(s). The leaders of the clans periodically meet in a room to select an overall best leader who has control over all the other leaders. This "Meeting Room Approach (MRA)" ensures a balance between the exploration and exploitation capabilities of the proposed NPO. NPO provides two steps for exploitation part, while the exploration is performed using another step. The local search of NPO is implemented using a unique distribution formula, while the global search ability contains a levy flight equation which generates a step for moving the families towards the new positions. The NPO was tested and evaluated based on sixty unconstrained benchmark test functions. Additionally, the scalability of the NPO was evaluated by solving eighteen large-scale problems. The experimental results confirmed that the proposed NPO performed better than some of the recent metaheuristics in terms of achieving the best solutions, scalability, time complexity, and convergence rate. The NPO successfully solved 52 out of 60 (86.6%) normal sized test functions while 16 out of 18 (88.8%) large-scale problems were equally solved. Good performances were also achieved with the NPO with respect to noise and limited information problems. A Wilcoxon Signed-Rank Test was performed to measure the pair-wise statistical performances of the algorithms and from the results, NPO recorded a better statistical performance compared to the other benchmarking algorithms. Conclusively, the experimental and statistical evaluations performed in this study proved the capability of the developed NPO in solving real-world optimization problems.

TABLE OF CONTENT

DECLARATION

TITLE PAGE

ACKNOWLEDGEMENTS **ii**

ABSTRAK **iii**

ABSTRACT **iv**

TABLE OF CONTENT **v**

LIST OF TABLES **viii**

LIST OF FIGURES **ix**

LIST OF SYMBOLS **x**

LIST OF ABBREVIATIONS **xi**

CHAPTER 1 INTRODUCTION **1**

1.1 Background 1

1.2 Problem Statement 3

1.3 Research Objectives 5

1.4 Research Scope 5

1.5 Research Limitations 6

1.6 Thesis Organization 6

CHAPTER 2 LITERATURE REVIEW **8**

2.1 Introduction 8

2.2 Optimization Problems 10

2.3 Metaheuristics 12

2.3.1 Exploration and Exploitation 14

2.3.2 Classification and Challenges of Metaheuristics 15
2.3.3 No Free Lunch Theorem 21
2.4 Nature-Inspired Algorithms 22
2.4.1 Swarm Intelligence 23
2.4.2 State of the Art in NIAs and SI 25
2.5 Gap Analysis 34
2.6 Summary 36

CHAPTER 3 RESEARCH METHODOLOGY 37

3.1 Introduction 37
3.2 Research Methodology 38
3.2.1 Literature Review 38
3.2.2 Methodology 39
3.2.3 Results and Discussion 39
3.3 Benchmark Functions 40
3.4 Experimental Settings 44
3.5 Summary 44

CHAPTER 4 NOMADIC PEOPLE OPTIMIZER 45

4.1 Introduction 45
4.2 Source of Inspiration 46
4.2.1 Nomadic People 46
4.2.2 The Bedouins 46
4.2.3 Observations and Rules 49
4.3 Mathematical Model of NPO 51
4.4 Graphical Illustration of NPO 59
4.4.1 Exploitation 59
4.4.2 Exploration 62
4.4.3 Graphical Illustration of Balancing Mechanism 65
4.5 Example: NPO for Solving Sphere Problem 70
4.6 Summary 75

CHAPTER 5 RESULTS AND DISCUSSION **76**

5.1 Introduction 76

5.2 Comparison and Simulation Settings 77

5.3 Results 78

5.3.1 NPO for unconstrained test functions 78

5.3.2 NPO for Large-Scale Problems 91

5.4 Convergence Analysis 96

5.5 Exploitation and Exploration Analysis 99

5.6 Discussion 101

5.7 Summary 106

CHAPTER 6 CONCLUSION AND FUTURE WORK **107**

6.1 Introduction 107

6.2 Research Summary 107

6.3 Conclusion 111

6.4 Suggestions for Future Works 112

6.4.1 Applications 112

6.4.2 Modifications 113

REFERENCES **115**

APPENDIX A metaheuristics used for comparIson **124**

APPENDIX B Multi-Swarm Particle Swarm Optimization (MPSO) **129**

LIST OF TABLES

Table 2.1	Metaheuristics and their characteristics	32
Table 2.2	Exploration, exploitation, and drawbacks of five metaheuristics	33
Table 3.1	Benchmark Test Functions used for evaluation	41
Table 3.2	The Equations for each benchmark test functions	42
Table 4.1	List of variables used in NPO	51
Table 4.2	Parameter Settings for the example	71
Table 5.1	The specific paramaters used in the studies metaheuristics	77
Table 5.2	Results of the metaheuristics over benchmark test functions	80
Table 5.3	Summarized comparison results of NPO verses other algorithms	85
Table 5.4	The rank of algorithm based on MAE	87
Table 5.5	The Wilcoxon Signed Rank Test	88
Table 5.6	Results for Large-scale problems, D = 100	92
Table 5.7	Results for Large-scale problems, D = 500	93
Table 5.8	Results for Large-scale problems, D = 1000	94
Table 5.9	Results for Large-scale problems, D = 2000	95
Table 5.10	Results of Exploration and Exploitation	100
Table 5.11	Comparison of time complexity	104

LIST OF FIGURES

Figure 2.1	Main concepts covered in Chapter Two	9
Figure 2.2	The architecture of an optimization problem	11
Figure 2.3	Types of optima	12
Figure 2.4	Classification of metaheuristics	17
Figure 2.5	Premature convergence	18
Figure 2.6	The 'No Free Lunch Theorem' (Engelbrecht, 2007)	22
Figure 2.7	The generalized pseudocode of SI-based algorithms	24
Figure 3.1	Research processes	38
Figure 4.1	The distribution of the Bedouins over Arabic countries	47
Figure 4.2	Semi-circular distribution of the families	50
Figure 4.3	Meeting Room Approach	56
Figure 4.4	Pseudocode of MRA	56
Figure 4.5	Pseudocode of NPO	57
Figure 4.6	Flowchart of NPO	58
Figure 4.7	Illustration of the first two steps of NPO	59
Figure 4.8	Illustration of the exploitation step of NPO	60
Figure 4.9	Illustration of the exploitation steps of NPO	60
Figure 4.10	Exploitation Analysis	61
Figure 4.11	Illustration of the first two steps of NPO	63
Figure 4.12	Illustration of the exploration and exploitation of NPO	63
Figure 4.13	Exploration Ability of NPO	64
Figure 4.14	MRA Balancing Mechanisim	67
Figure 4.15	Simulation of all NPO operators	70
Figure 4.16	Sphere Test Function	71
Figure 5.1	3D illustration of some benchmark test functions	79
Figure 5.2	The results of all tests	85
Figure 5.3	The results of unimodal tests	85
Figure 5.4	The results of multimodal tests	86
Figure 5.5	Convergence curves for functions($f7, f16, f21, f26, f34, f60$)	99
Figure 5.6	Exploration and exploitation of NPO	102
Figure 5.7	Convergence curve for $f13$	103
Figure 5.8	Time-based comparison between all metaheuristics	105

LIST OF SYMBOLS

f_i	Objective function
X_i	The variables of the problem
Max	Maximizing Problem
Min	Minimizing Problem
σ	Sheikh of the Clan
$\overrightarrow{\sigma_c}$	The position of the Sheikh
UB	Upper Bound
LB	Lower Bound
$\overrightarrow{x_i}$	The position of a family
$Rand$	Random value between 0 and 1
Rd	Reduce of the circle
θ	The value of the angle
Ψ	The direction variable
a_c	Area of the clan

LIST OF ABBREVIATIONS

SBA	Swarm-Based Algorithms
PBA	Physics-Based Algorithms
EA	Evolutionary Algorithms
GA	Genetic Algorithms
GP	Genetic Programming
ES	Evolutionary Strategies
PSO	Particle Swarm Optimization
ABC	Artificial Bees Colony
FFA	Firefly Algorithm
BA	Bat Algorithm
GWO	Grey Wolf Optimizer
BFO	Bacterial Foraging Optimization
CSA	Cuckoo Search Algorithm
FSO	Fish Swarm Optimization
ABO	African Buffalo Algorithm
TLBO	Teaching-Learning-Based Optimizer
SELO	Socio-Evolution & Learning Optimizer
CEA	Cultural Evolution Algorithm
WC	Water Cycle
SA	Simulated Annealing
GSA	Gravitational Search Algorithms
MB	Mine Blast
NPO	Nomadic People Optimizer
MRA	Meeting Room Approach
U-N	Unimodal None Separable
U-S	Unimodal Separable
M-N	Multimodal None Separable
M-S	Multimodal Separable
NIAs	Nature-Inspired Algorithms
NNIAs	Non-Nature-Inspired Algorithms
SOM	Single Objective Metaheuristics
MOM	Multi-Objective Metaheuristics

REFERENCES

Abdel-Basset, M., Abdel-Fatah, L., & Sangaiah, A. K. (2018). Metaheuristic algorithms a comprehensive review. In *Computational Intelligence for Multimedia Big Data on the Cloud with Engineering Applications* (pp. 185–231). Elsevier. https://doi.org/10.1016/C2016-0-03919-0

Agarwal, P., & Mehta, S. (2014). Nature-inspired algorithms: state-of-art, problems and prospects. *International Journal of Computer Applications*, *100*(14), 14–21. https://doi.org/10.5120/17593-8331

Ahmadi-Javid, A. (2011). Anarchic Society Optimization: A human-inspired method. In *Proceddings of IEEE Congress of Evolutionary Computation (CEC 2011)* (pp. 2586–2592). https://doi.org/10.1109/CEC.2011.5949940

Akay, B., & Karaboga, D. (2012). Artificial bee colony algorithm for large-scale problems and engineering design optimization. *Journal of Intelligent Manufacturing*. https://doi.org/10.1007/s10845-010-0393-4

Al-Dabbagh, R. D., Neri, F., Idris, N., & Baba, M. S. (2018). Algorithmic design issues in adaptive differential evolution schemes: review and taxonomy. *Swarm and Evolutionary Computation*. https://doi.org/10.1016/J.SWEVO.2018.03.008

Alshamlan, H. M. (2018). Co-ABC: Correlation artificial bee colony algorithm for biomarker gene discovery using gene expression profile. *Saudi Journal of Biological Sciences*. https://doi.org/10.1016/j.sjbs.2017.12.012

Alshamlan, H. M., Badr, G. H., & Alohali, Y. A. (2015). Genetic bee colony (GBC) algorithm: a new gene selection method for microarray cancer classification. *Computational Biology and Chemistry*. https://doi.org/10.1016/j.compbiolchem.2015.03.001

Andrei, N. (2008). An unconstrained optimization test functions collection. *Advanced Modelling and Optimization*, *10*(1), 147–161.

Atashpaz-Gargari, E., & Lucas, C. (2007). Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition. In *Proceedings of IEEE Congress on Evolutionary Computation, (CEC 2007)* (pp. 4661–4667). https://doi.org/10.1109/CEC.2007.4425083

Aydilek, İ. B. (2018). A hybrid firefly and particle swarm optimization algorithm for computationally expensive numerical problems. *Applied Soft Computing Journal*, *66*, 232–249. https://doi.org/10.1016/j.asoc.2018.02.025

Azrag, M. A. K., Kadir, T. A. A., Odili, J. B., & Essam, M. H. A. (2017). A global african buffalo optimization. *International Journal of Software Engineering and Computer Systems*, *3*(3), 138–145.

Barták, R., Salido, M. A., & Rossi, F. (2010). Constraint satisfaction techniques in planning and scheduling. *Journal of Intelligent Manufacturing*, *21*(1), 5–15. https://doi.org/10.1007/s10845-008-0203-4

Beni, G., & Wang, J. (1991). Theoretical problems for the realization of distributed robotic systems. In *Proceedings of International Conference on Robotics and Automation* (pp. 1914–1920). Sacramento, CA, USA,: IEEE.

Bénichou, O., Loverdo, C., Moreau, M., & Voituriez, R. (2006). Two-dimensional intermittent search processes: an alternative to lévy flight strategies. *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, *74*(2). https://doi.org/10.1103/PhysRevE.74.020102

Bénichou, O., Loverdo, C., Moreau, M., & Voituriez, R. (2011). Intermittent search strategies. *Reviews of Modern Physics*, *83*(1), 81–129. https://doi.org/10.1103/RevModPhys.83.81

Benkercha, R., Moulahoum, S., & Kabache, N. (2017). Combination of artificial neural network and flower pollination algorithm to model fuzzy logic MPPT Controller for Photovoltaic systems. In *Proceedings of 18th International Symposium on Electromagnetic Fields in Mechatronics, Electrical and Electronic Engineering (ISEF)* (pp. 1–2). IEEE.

Beyer, H. G., Finck, S., & Breuer, T. (2014). Evolution on trees: on the design of an evolution strategy for scenario-based multi-period portfolio optimization under transaction costs. *Swarm and Evolutionary Computation*, *17*, 74–87. https://doi.org/10.1016/j.swevo.2014.03.002

Birattari, M., Paquete, L., St, T., & Varrentrapp, K. (2001). Classification of metaheuristics and design of experiments for the analysis of components. *Technology*.

Blum, C., & Roli, A. (2003). Metaheuristics in combinatorial optimization: overview and conceptual comparison. *ACM Computing Surveys*, *35*(3), 189–213. https://doi.org/10.1007/s10479-005-3971-7

Bonabeau, E., Dorigo, M., & Theraulaz, G. (1999). *Swarm intelligence: from natural to artificial systems*. *Journal of Artificial Societies and Social Simulation* (Vol. 4). https://doi.org/10.1080/09540090210144948

Boussaïd, I., Lepagnot, J., & Siarry, P. (2013). A survey on optimization metaheuristics. *Information Sciences*, *237*, 82–117. https://doi.org/10.1016/j.ins.2013.02.041

Caraffini, F., Neri, F., & Iacca, G. (2017). Large scale problems in practice: the effect of dimensionality on the interaction among variables. In *Proceedings of European Conference on the Applications of Evolutionary Computation* (pp. 636–652). Springer, Cham.

Chakraborty, D., Saha, S., & Maity, S. (2015). Training feedforward neural networks using hybrid flower pollination-gravitational search algorithm. In *Proceedings of International Conference on Futuristic Trends on Computational Analysis and Knowledge Management (ABLAZE)* (pp. 261–266). IEEE. https://doi.org/10.1109/ABLAZE.2015.7155008

Clerc, M. (2011). Standard PSO 2011 (SPSO). Retrieved from https://www.particleswarm.info/Programs.html

Colorni, A., Dorigo, M., & Maniezzo, V. (1991). Distributed optimization by ant colonies. In *Proceedings of the 1st European Conference on Artificial Life* (Vol. 142, pp. 134–142). https://doi.org/10.1016/S0303-2647(97)01708-5

Črepinšek, M., Liu, S.-H., & Mernik, M. (2013). Exploration and Exploitation in Evolutionary Algorithms: A Survey. *ACM Computing Surveys*, *45*(3), 35:1-35:33. https://doi.org/10.1145/2480741.2480752

Deneubourg, J. L., & Goss, S. (1989). Collective patterns and decision-making. *Ethology Ecology and Evolution*, *1*(4), 295–311. https://doi.org/10.1080/08927014.1989.9525500

Deneubourg, J. L., Goss, S., Franks, N., Sendova-Franks, A., Detrain, C., & Chrétien, L. (1991).

The fynamics of collective sorting robot - like ants and ant - like robots. In *Proceedings of the 1st International Conference on Simulation of Adaptive Behavior on From Animals to Animats* (pp. 356–363). MIT Press.

Dorigo, M. (1992). *Optimization, learning and natural algorithms*. Politecnico di Milano.

Dorigo, M., Maniezzo, V., & Colorni, A. (1996). Ant system: optimization by a colony of cooperating agents. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, *26*(1), 29–41. https://doi.org/10.1109/3477.484436

Eberhart, R., & Kennedy, J. (1995). A new optimizer using particle swarm theory. In *Proceedings of the 6th International Symposium on Micro Machine and Human Science (MHS 95)* (pp. 39–43). IEEE. https://doi.org/10.1109/MHS.1995.494215

Eiben, A. E., & Smit, S. K. (2011). Parameter tuning for configuring and analyzing evolutionary algorithms. *Swarm and Evolutionary Computation*. https://doi.org/10.1016/j.swevo.2011.02.001

El-Shorbagy, M. A., & Hassanien, A. E. (2018). Particle swarm optimization from theory to applications. *International Journal of Rough Sets and Data Analysis (IJRSDA)*, *5*(2), 1–24.

Emami, H., & Derakhshan, F. (2015). Election algorithm: a new socio-politically inspired strategy. *AI Communications*, *28*(3), 591–603. https://doi.org/10.3233/AIC-140652

Engelbrecht, A. P. (2007). *Computational Intelligence : An Introduction* (2nd ed.). John Wiley & Sons. https://doi.org/10.1002/9780470512517

Fister, I., Yang, X. S., Brest, J., & Fister, D. (2013). A brief review of nature-inspired algorithms for optimization. *Elektrotehniski Vestnik/Electrotechnical Review*, *80*(3), 116–122.

Fister, I., Yang, X. S., Fister, D., & Fister, I. (2014). Cuckoo search: A brief literature review. In *Studies in Computational Intelligence* (Vol. 516, pp. 49–62). https://doi.org/10.1007/978-3-319-02141-6_3

Formato, R. A. (2014). Central force optimization algorithm. *Intelligent Systems Reference Library*, *62*, 333–337. https://doi.org/10.1007/978-3-319-03404-1_19

Gandomi, A. H., Yang, X. S., Talatahari, S., & Alavi, A. H. (2013). Firefly algorithm with chaos. *Communications in Nonlinear Science and Numerical Simulation*, *18*(1), 89–98. https://doi.org/10.1016/j.cnsns.2012.06.009

Gendreau, M., & Potvin, J.-Y. (2018). *Handbook of metaheuristics* (Vol. 57). https://doi.org/10.1007/b101874

Gupta, S., & Deep, K. (2018). A novel random walk grey wolf optimizer. *Swarm and Evolutionary Computation*. https://doi.org/10.1016/j.swevo.2018.01.001

Heidari, A. A., & Pahlavani, P. (2017). An efficient modified grey wolf optimizer with Lévy flight for optimization tasks. *Applied Soft Computing Journal*, *60*, 115–134. https://doi.org/10.1016/j.asoc.2017.06.044

Ho, Y. C., & Pepyne, D. L. (2002). Simple explanation of the no-free-lunch theorem and its implications. *Journal of Optimization Theory and Applications*, *115*(3), 549–570. https://doi.org/10.1023/A:1021251113462

Holland, J. H. (1975). Adaptation in natural and artificial systems. *Ann Arbor MI University of Michigan Press*, *Ann Arbor*, 183. https://doi.org/10.1137/1018105

Huan, T. T., Kulkarni, A. J., Kanesan, J., Huang, C. J., & Abraham, A. (2017). Ideology algorithm: a socio-inspired optimization methodology. *Neural Computing and Applications*, *28*, 845–876. https://doi.org/10.1007/s00521-016-2379-4

Hussain, K., Salleh, M. N. M., Cheng, S., & Shi, Y. (2018). Metaheuristic research: a comprehensive survey. *Artificial Intelligence Review*, 1–43.

Husseinzadeh Kashan, A. (2014). League championship algorithm (LCA): An algorithm for global optimization inspired by sport championships. *Applied Soft Computing Journal*, *16*, 171–200. https://doi.org/10.1016/j.asoc.2013.12.005

Jamil, M., Yang, X. S., & Zepernick, H. J. D. (2013). Test functions for global optimization: a comprehensive survey (Book Chapter). In *Swarm Intelligence and Bio-Inspired Computation* (pp. 193–222). Elsevier. https://doi.org/10.1016/B978-0-12-405163-8.00008-9

Kallioras, N. A., Lagaros, N. D., & Avtzis, D. N. (2018). Pity beetle algorithm – a new metaheuristic inspired by the behavior of bark beetles. *Advances in Engineering Software*, *121*, 147–166. https://doi.org/10.1016/j.advengsoft.2018.04.007

Karaboga, D. (2005). An idea based on honey bee swarm for numerical optimization. *Technical Report TR06, Erciyes University*, (TR06), 10. https://doi.org/citeulike-article-id:6592152

Karaboga, D., & Basturk, B. (2007). A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm. *Journal of Global Optimization*, *39*(3), 459–471. https://doi.org/10.1007/s10898-007-9149-x

Karaboga, D., Gorkemli, B., Ozturk, C., & Karaboga, N. (2014). A comprehensive survey: Artificial bee colony (ABC) algorithm and applications. *Artificial Intelligence Review*, *42*(1), 21–57. https://doi.org/10.1007/s10462-012-9328-0

Kashan, A. H. (2009). League championship algorithm: a new algorithm for numerical function optimization. In *Proceedings of International Conference on Soft Computing and Pattern Recognition (SoCPaR 2009)* (pp. 43–48). https://doi.org/10.1109/SoCPaR.2009.21

Kashif, H., Salleh, N., Cheng, S., & Shi, Y. (2018). On the exploration and exploitation in popular swarm-based metaheuristic algorithms. *Neural Computing and Applications*, 1–19.

Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of International Conference on Neural Networks (ICNN'95)* (Vol. 4, pp. 1942–1948 vol.4). IEEE. https://doi.org/10.1109/ICNN.1995.488968

Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by simulated annealing. *Science*, *220*(4598), 671–680. https://doi.org/10.1126/science.220.4598.671

Köppen, M., Wolpert, D. H., & Macready, W. G. (2001). Remarks on a recent paper on the "no free lunch" theorems. *IEEE Transactions on Evolutionary Computation*, *5*(3), 295–296. https://doi.org/10.1109/4235.930318

Koziel, S., & Yang, X. S. (2011). *Computational optimization, methods and algorithms*. *Springer*. https://doi.org/10.1007/978-3-642-20859-1

Kulkarni, A. J., Krishnasamy, G., & Abraham, A. (2016). Socio-inspired optimization using cohort intelligence (Book Chapter). In *Cohort Intelligence: A Socio-inspired Optimization Method* (Vol. 114, pp. 9–24). https://doi.org/10.1007/978-3-319-44254-9_2

Kumar, M., Kulkarni, A. J., & Satapathy, S. C. (2017). Socio evolution & learning optimization algorithm: A socio-inspired optimization methodology. *Future Generation Computer Systems*, *81*, 252–272. https://doi.org/10.1016/j.future.2017.10.052

Kuo, H. C., & Lin, C. H. (2013). Cultural evolution algorithm for global optimizations and its applications. *Journal of Applied Research and Technology*, *11*(4), 510–522. https://doi.org/10.1016/S1665-6423(13)71558-X

Li, X., Shao, Z., & Qian, J. (2002). An optimizing method based on autonomous animats: fish-swarm algorithm. *Systems Engineering: Theory and Practice*, *22*(11), 32–38. Retrieved from http://en.cnki.com.cn/Article_en/CJFDTOTAL-XTLL200211006.htm

Luke, S. (2013). *Essentials of metaheuristics*. *Optimization*. https://doi.org/10.1007/s10710-011-9139-0

Lv, W., He, C., Li, D., Cheng, S., Luo, S., & Zhang, X. (2010). Election campaign optimization algorithm. In *Proceedings of International Conference on Computational Science (ICCS 2010)* (Vol. 1, pp. 1377–1386). Elsevier. https://doi.org/10.1016/j.procs.2010.04.153

Lynn, N., & Suganthan, P. N. (2017). Ensemble particle swarm optimizer. *Applied Soft Computing*, *55*, 533–548. https://doi.org/10.1016/j.asoc.2017.02.007

Mirjalili, S. (2015). The ant lion optimizer. *Advances in Engineering Software*, *83*, 80–98. https://doi.org/10.1016/j.advengsoft.2015.01.010

Mirjalili, S. (2016). SCA: A sine cosine algorithm for solving optimization problems. *Knowledge-Based Systems*, *96*, 120–133. https://doi.org/10.1016/j.knosys.2015.12.022

Mirjalili, S., Gandomi, A. H., Mirjalili, S. Z., Saremi, S., Faris, H., & Mirjalili, S. M. (2017). Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems. *Advances in Engineering Software*, *114*, 163–191. https://doi.org/10.1016/j.advengsoft.2017.07.002

Mirjalili, S., & Hashim, S. Z. M. (2010). A new hybrid PSOGSA algorithm for function optimization. In *Proceedings of International Conference on Computer and Information Application (ICCIA 2010)* (pp. 374–377). IEEE. https://doi.org/10.1109/ICCIA.2010.6141614

Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. *Advances in Engineering Software*, *69*, 46–61. https://doi.org/10.1016/j.advengsoft.2013.12.007

Mirjalili, S., Mohd Hashim, S. Z., & Moradian Sardroudi, H. (2012). Training feedforward neural networks using hybrid particle swarm optimization and gravitational search algorithm. *Applied Mathematics and Computation*, *218*(22), 11125–11137. https://doi.org/10.1016/j.amc.2012.04.069

Moosavian, N., & Kasaee Roodsari, B. (2014). Soccer league competition algorithm: A novel meta-heuristic algorithm for optimal design of water distribution networks. *Swarm and Evolutionary Computation*, *17*, 14–24. https://doi.org/10.1016/j.swevo.2014.02.002

Mortazavi, A., Toğan, V., & Nuhoğlu, A. (2018). Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems. *Engineering*

Applications of Artificial Intelligence. https://doi.org/10.1016/j.engappai.2018.03.003

Mousavirad, S. J., & Ebrahimpour-Komleh, H. (2017). Human mental search: a new population-based metaheuristic optimization algorithm. *Applied Intelligence*, *47*(3), 850–887. https://doi.org/10.1007/s10489-017-0903-6

Niu, B., Zhu, Y., He, X., & Wu, H. (2007). MCPSO: A multi-swarm cooperative particle swarm optimizer. *Applied Mathematics and Computation*, *185*(2), 1050–1062. https://doi.org/10.1016/j.amc.2006.07.026

Odili, J. B., Kahar, M. N. M., & Anwar, S. (2015). African buffalo optimization: a swarm-intelligence technique. In *Proceedings of International Symposium on Robotics and Intelligent Sensors (IRIS2015)* (Vol. 76, pp. 443–448). IEEE.

Passino, K. M. (2002). Biomimicry of bacterial foraging for distributed optimization and control. *Control Systems, IEEE*, *22*(3), 52–67. https://doi.org/10.1109/MCS.2002.1004010

Qu, B. Y., Liang, J. J., Wang, Z. Y., Chen, Q., & Suganthan, P. N. (2016). Novel benchmark functions for continuous multimodal optimization with comparative results. *Swarm and Evolutionary Computation*, *26*, 23–34. https://doi.org/10.1016/j.swevo.2015.07.003

Rao, R. V., Savsani, V. J., & Vakharia, D. P. (2011). Teaching–learning-based optimization: A novel method for constrained mechanical design optimization problems. *Computer-Aided Design*, *43*(3), 303–315. https://doi.org/10.1016/j.cad.2010.12.015

Rao, R. V., Savsani, V. J., & Vakharia, D. P. (2012). Teaching-Learning-Based Optimization: an optimization method for continuous non-linear large scale problems. *Information Sciences*, *183*(1), 1–15. https://doi.org/10.1016/j.ins.2011.08.006

Rashedi, E., Nezamabadi-pour, H., & Saryazdi, S. (2009). GSA: A gravitational search algorithm. *Information Sciences*, *179*(13), 2232–2248. https://doi.org/10.1016/j.ins.2009.03.004

Ray, T., & Liew, K. M. (2003). Society and civilization: an optimization algorithm based on the simulation of social behavior. *IEEE Transactions on Evolutionary Computation*, *7*(4), 386–396. https://doi.org/10.1109/TEVC.2003.814902

Reynolds, C. W. (1987). Flocks, herds and schools: A distributed behavioral model. *ACM SIGGRAPH Computer Graphics*, *21*(4), 25–34. https://doi.org/10.1145/37402.37406

Reynolds, R. G., & Sverdlik, W. (1994). Problem solving using cultural algorithms. In *Proceedings of the 1st IEEE Conference on Evolutionary Computation. IEEE World Congress on Computational Intelligence* (pp. 645–650). IEEE. https://doi.org/10.1109/ICEC.1994.349983

Saka, M. P., Doğan, E., & Aydogdu, I. (2013). Analysis of swarm intelligence-based algorithms for constrained optimization (Book Chapter). In *Swarm Intelligence and Bio-Inspired Computation* (pp. 25–48). https://doi.org/10.1016/B978-0-12-405163-8.00002-8

Salgotra, R., & Singh, U. (2017). Application of mutation operators to flower pollination algorithm. *Expert Systems with Applications*, *79*, 112–129. https://doi.org/10.1016/j.eswa.2017.02.035

Satapathy, S., & Naik, A. (2016). Social group optimization (SGO): a new population evolutionary optimization technique. *Complex & Intelligent Systems*, *2*(3), 173–203. https://doi.org/10.1007/s40747-016-0022-8

Shi, J., & Zhang, Q. (2018). A new cooperative framework for parallel trajectory-based metaheuristics. *Applied Soft Computing*, *65*, 374–386. https://doi.org/10.1016/j.asoc.2018.01.022

Shi, Y., & Eberhart, R. C. (1999). Empirical study of particle swarm optimization. In *Proceedings of IEEE Congress on Evolutionary Computation (CEC 99)* (Vol. 3, p. 1945–1950 Vol. 3). IEEE. https://doi.org/10.1109/CEC.1999.785511

Siddique, N., & Adeli, H. (2015). Nature inspired computing: an overview and some future directions. *Cognitive Computation*, *7*(6), 706–714. https://doi.org/10.1007/s12559-015-9370-8

Silberholz, J., & Golden, B. (2010). Comparison of metaheuristics. *Handbook of Metaheuristics*, 625–640.

Slowik, A., & Kwasnicka, H. (2018). Nature inspired methods and their industry applications – swarm intelligence algorithms. *IEEE Transactions on Industrial Informatics*, *14*(3), 1004–1015. https://doi.org/10.1109/TII.2017.2786782

Socha, K., & Dorigo, M. (2008). Ant colony optimization for continuous domains. *European Journal of Operational Research*, *185*(3), 1155–1173. https://doi.org/10.1016/j.ejor.2006.06.046

Sörensen, K., Sevaux, M., & Glover, F. (2018). A history of metaheuristics. *Handbook of Heuristics*, 1–18.

Talbi, E. G. (2009). *Metaheuristics: from design to implementation*. Wiley. https://doi.org/10.1002/9780470496916

Ursem, K. R. (2003). *Models for Evolutionary Algorithms and their Applications in System Identification and Control Optimization*. University of Aarhus, Denmark.

Wang, H., Wang, W., Zhou, X., Sun, H., Zhao, J., Yu, X., & Cui, Z. (2017). Firefly algorithm with neighborhood attraction. *Information Sciences*, *382–383*, 374–387. https://doi.org/10.1016/j.ins.2016.12.024

Wang, Y. (2010). A sociopsychological perspective on collective intelligence in metaheuristic computing. *International Journal of Applied Metaheuristic Computing*, *1*(1), 110–128. https://doi.org/10.4018/jamc.2010102606

Weise, T. (2009). Global optimization algorithms–theory and application. *Self-Published*, *1*, 820. https://doi.org/doi=10.1.1.64.8184

Weise, T., Zapf, M., Chiong, R., & Nebro, A. J. (2009). Why is optimization difficult? In R. Chiong (Ed.), *Nature-Inspired Algorithms for Optimisation* (pp. 1–50). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-00267-0_1

Wolpert, D. H., & Macready, W. G. (1997). No free lunch theorems for optimization. *IEEE Transactions on Evolutionary Computation*, *1*(1), 67–82. https://doi.org/10.1109/4235.585893

Xu, Y., Cui, Z., & Zeng, J. (2010). Social emotional optimization algorithm for nonlinear constrained optimization problems. *Swarm, Evolutionary, and Memetic Computing. Springer Berlin Heidelberg*, 583–590.

Yadav, A., Deep, K., Kim, J. H., & Nagar, A. K. (2016). Gravitational swarm optimizer for global optimization. *Swarm and Evolutionary Computation*, *31*, 64–89. https://doi.org/10.1016/j.swevo.2016.07.003

Yang, X. S. (2008). *Firefly algorithm for multimodal optimization*. *Nature-Inspired Metaheuristic Algorithms*. Luniver Press.

Yang, X. S. (2009). Firefly algorithms for multimodal optimization. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *5792 LNCS*, 169–178. https://doi.org/10.1007/978-3-642-04944-6_14

Yang, X. S. (2010a). A new metaheuristic bat-inspired algorithm (Book Chapter). In *Studies in Computational Intelligence* (Vol. 284, pp. 65–74). https://doi.org/10.1007/978-3-642-12538-6_6

Yang, X. S. (2010b). *Engineering optimization: an introduction with metaheuristic applications*. Wiley. https://doi.org/10.1002/9780470640425

Yang, X. S. (2010c). *Nature-inspired metaheuristic algorithms* (2nd ed.). Luniver press. https://doi.org/10.1016/B978-0-12-416743-8.00005-1

Yang, X. S. (2011). Metaheuristic optimization: algorithm analysis and open problems. In *Proceedings of International Symposium on Experimental Algorithms* (pp. 21–32).

Yang, X. S. (2012). Flower pollination algorithm for global optimization. In *Proceedings of International Conference on Unconventional Computing and Natural Computation.* (pp. 240–249). Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-642-32894-7_27

Yang, X. S. (2013). Metaheuristic optimization: nature-inspired algorithms and applications. *Studies in Computational Intelligence*. https://doi.org/10.1007/978-3-642-29694-9-16

Yang, X. S. (2014). *Nature-inspired optimization algorithms*. Elsevier. https://doi.org/10.1016/C2013-0-01368-0

Yang, X. S., & Deb, S. (2009). Cuckoo search via lévy flights. In *Proceedings of World Congress on Nature & Biologically Inspired Computing (NaBIC)* (pp. 210–214). https://doi.org/10.1109/NABIC.2009.5393690

Yang, X. S., & Deb, S. (2014). Cuckoo search: recent advances and applications. *Neural Computing and Applications*, *24*(1), 169–174. https://doi.org/10.1007/s00521-013-1367-1

Yang, X. S., Deb, S., Fong, S., He, X., & Zhao, Y. X. (2016). From swarm intelligence to metaheuristics: nature-inspired optimization algorithms. *Computer*, *49*(9), 52–59. https://doi.org/10.1109/MC.2016.292

Yang, X. S., Deb, S., & He, X. (2013). Eagle strategy with flower algorithm. In *Proceedings of the International Conference on Advances in Computing, Communications and Informatics (ICACCI 2013)* (pp. 1213–1217). https://doi.org/10.1109/ICACCI.2013.6637350

Yang, X. S., Deb, S., Loomes, M., & Karamanoglu, M. (2013). A framework for self-tuning optimization algorithm. *Neural Computing and Applications*, *23*(7–8), 2051–2057. https://doi.org/10.1007/s00521-013-1498-4

Yang, X. S., Deb, S., Zhao, Y.-X., Fong, S., & He, X. (2017). Swarm intelligence: past, present and future. *Soft Computing*, *22*(18), 5923–5933. https://doi.org/10.1007/s00500-017-28105

Yang, X. she. (2010). Firefly algorithm, Levy flights and global optimization (Book Chapter). In *Research and Development in Intelligent Systems* (pp. 209–218). https://doi.org/10.1007/978-1-84882-983-1

Yaseen, Z. M., Ebtehaj, I., Bonakdari, H., Deo, R. C., Danandeh Mehr, A., Mohtar, W. H. M. W., Diop, L., El-shafie, A., & Singh, V. P. (2017). Novel approach for streamflow forecasting using a hybrid ANFIS-FFA model. *Journal of Hydrology*, *554*, 263–276. https://doi.org/10.1016/j.jhydrol.2017.09.007

Zhang, L., Shan, L., & Wang, J. (2017). Optimal feature selection using distance-based discrete firefly algorithm with mutual information criterion. *Neural Computing and Applications*, *28*(9), 2795–2808. https://doi.org/10.1007/s00521-016-2204-0

Zhang, Y., & Wu, L. (2011). A hybrid TS-PSO optimization algorithm. *Journal of Convergence Information Technology*, *6*(5), 169–174. https://doi.org/10.4156/jcit.vol6.issue5.18

Zong, W. G., Joong, H. K., & Loganathan, G. V. (2001). A new heuristic optimization algorithm: harmony search. *Simulation*, *76*(2), 60–68. https://doi.org/10.1177/003754970107600201